ISTA 421 / INFO 521 – Final Project OPTION A: Metropolis-Hastings MCMC Inference of 3D Line

Due: Friday, December 8, 8pm

Total 20% of final grade

Austin Young Undergraduate

1. To run the script simply run: `Final.py`. The script will automatically run through each function in order, saving the MH generated samples and figures as it runs. The script will also show each generated graph, pausing the script in the process, which can provide a viewer the opportunity to check the output for the MAP estimates. Otherwise the MAP outputs will still result and will be differentiated according to `print()` outputs. Each task is functionalized to run independently and is labelled according to the task number. To run only a specific task, or prevent the samples from being saved due to memory constraints, –task (1-5) and –save (True or False) can be provided as arguements to determine the script runtime configurations. –task 1 will run all tasks in sequence, the defaults are –task 1 and –save True.

2. The plot of the accepted proposals for p_i shows the evolution of the x, y, z values of p_i. As samples are drawn from the MH algorithm, these coordinate values roughly converge to certain values more closely approximating the true distribution values.

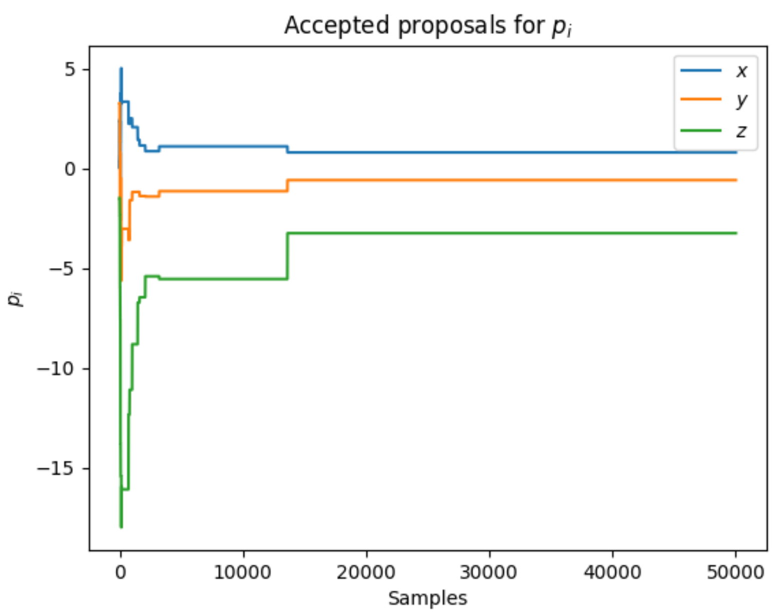

Figure 1: Accepted p_i samples from the MH algorithm for 50,000 iterations.

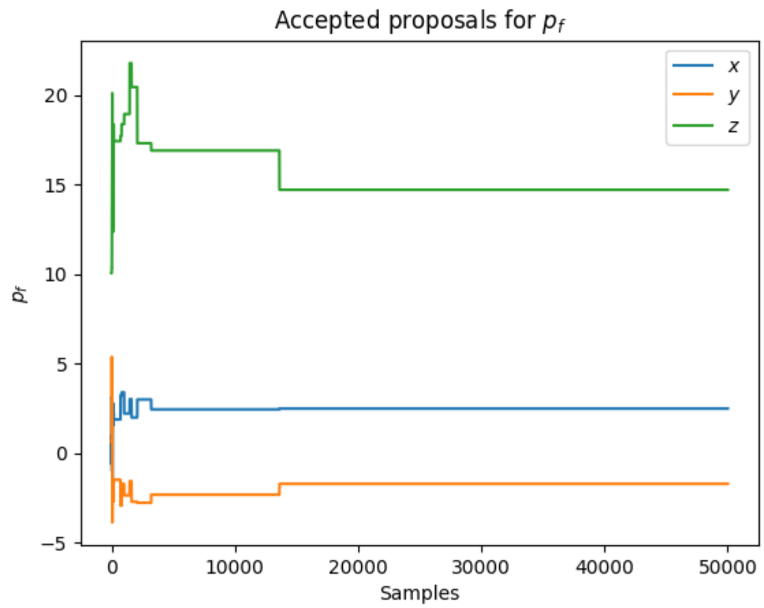

Figure 2: Accepted p_f samples from the MH algorithm for 50,000 iterations.

3. MAP estimate of the 3d endpoint p_i [0.91800215 -0.78783157 -4.09102543] corresponding to (x, y, z) coordinates.
   MAP estimate of the 3d endpoint p_f [2.47778969 -1.87512867 15.37687865]

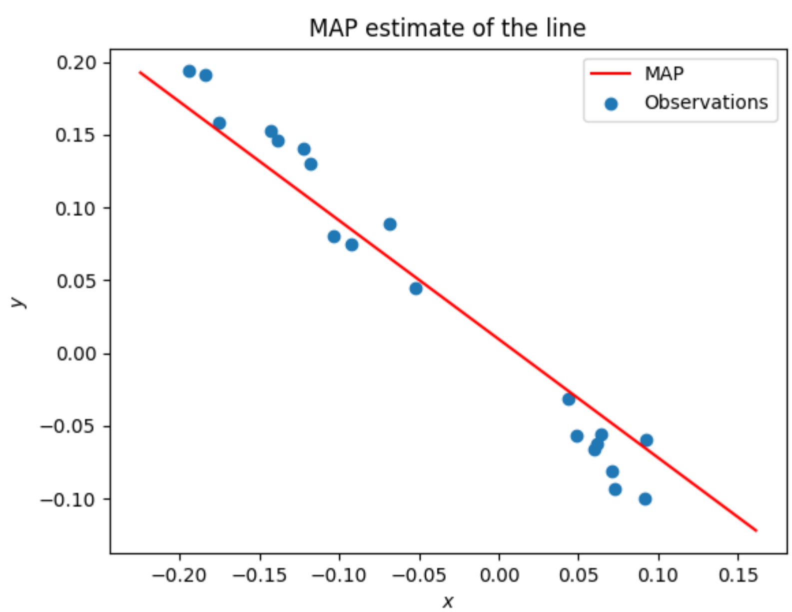

Figure 3: The MAP estimate of the line based on the 2D projected p_i and p_f endpoints compared to the noisy observations as viewed from Camera 1.

4. 4

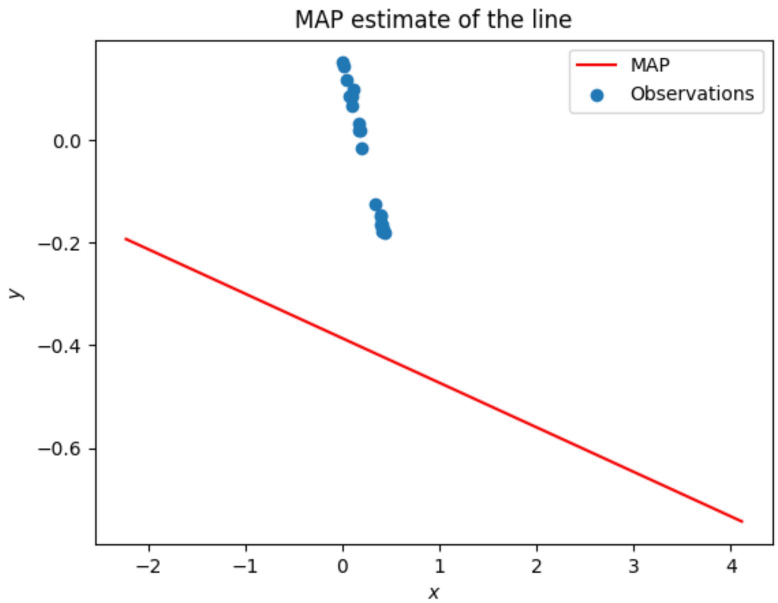

Figure 4: The original MAP estimation from the data of the first camera plotted against the perspective of the second camera. This new perspective fits the MAP estimate extremely poorly.

5. MAP estimate of the 3D endpoint p_i resampled using both cameras [-1.30405385 0.97642247 5.43348815]
   MAP estimate of the 3D enpoint p_f [0.62320022 -0.84635954 7.07749965]

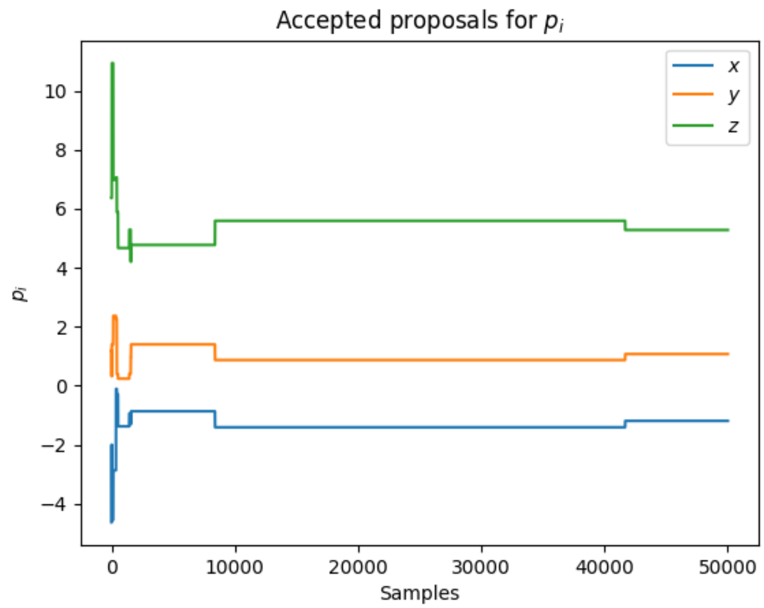

Figure 5: Accepted p_i samples from the MH algorithm for 50,000 iterations using both cameras.

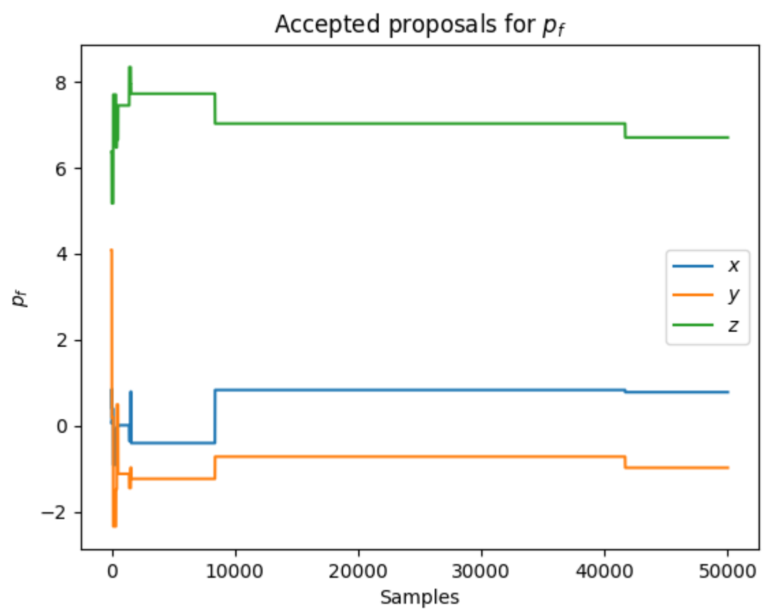

Figure 6: Accepted p_f samples from the MH algorithm for 50,000 iterations using both cameras.

The graphs look structurally similar, as the variance for each line varies considerably at the start, has smaller perturbations as time goes, and synchronizes the changes in p values. In terms of differences, the second p_i graph is more spread out between terms and faster to converge. The second p_f graph is also more spread out between terms, but is closer in similarity to the first MH estimations.

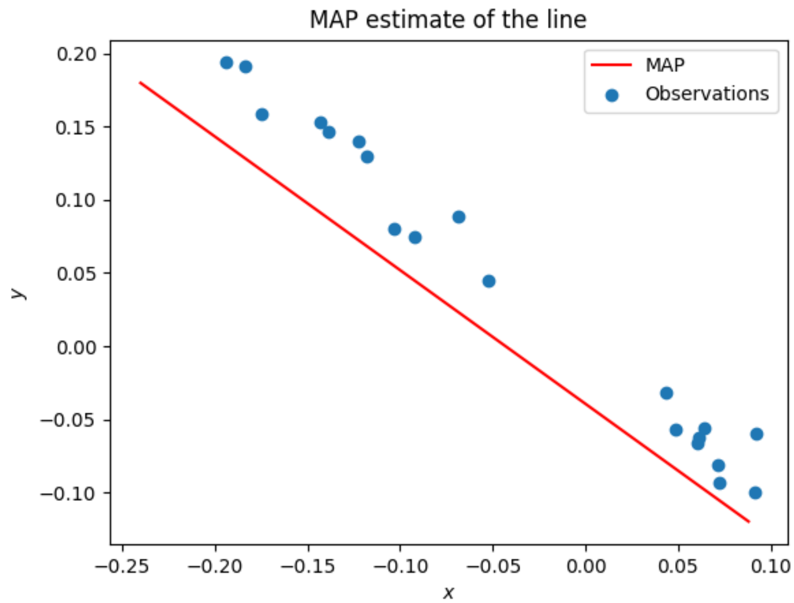

Figure 7: The new MAP estimate using both camera's perspectives plotted against only *camera 1* observations.

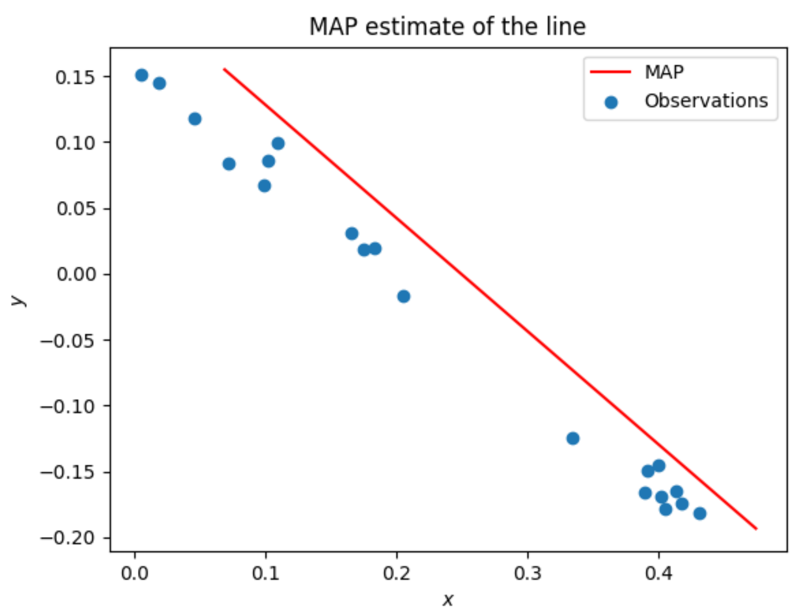

Figure 8: The new MAP estimate using both camera's perspectives plotted against only *camera 2* observations.

The new MAP estimates for the camera 1 observations fits worse than the MAP estimate using only the camera 1 observations. This result follows the basic understanding of bias/variance, as this newly re-sampled MAP estimate is made more generalizable by requiring a fit for both camera perspectives. In this generalization, the MAP estimate for the camera 2 observations fits much better.